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Working Paper 91
http://ceep.bit.edu.cn/english/publications/wp/index.htm

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March 2016

This paper can be cited as: *Wang K, Xian y, Wei Y-M, Huang Z. 2016. Sources of carbon productivity change: A decomposition and disaggregation analysis based on global Luenberger productivity indicator and endogenous directional distance functionCEEP-BIT Working Paper.*

The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China (grant nos. 71471018, 71101011 and 71521002). The views expressed herein are those of the authors and do not necessarily reflect the views of the Center for Energy and Environmental Policy Research.

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# Sources of carbon productivity change: A decomposition and disaggregation analysis based on global Luenberger productivity indicator and endogenous directional distance function

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**Abstract:** The measurement of carbon productivity makes the effort of global climate change mitigation accountable and helps to formulate policies and prioritize actions for economic growth, energy conservation, and carbon emissions control. Previous studies arbitrarily predetermined the directions of directional distance function in calculating the carbon productivity indicator, and the traditional carbon productivity indicator itself is not capable of identifying the contribution of different energy driven carbon emissions in carbon productivity change. Through utilizing an endogenous directional distance function selecting approach and a global productivity index, this paper proposes a global Luenberger carbon productivity indicator for computing carbon productivity change. This carbon productivity indicator can be further decomposed into three components that respectively identify the best practice gap change, pure efficiency change, and scale efficiency change. Moreover, the carbon productivity indicator is shown as a combination of individual carbon emissions productivity indicators that account for the contribution of different fossil fuel driven carbon emissions (i.e. coal driven $CO_2$, oil driven $CO_2$, and natural gas driven $CO_2$) toward the carbon productivity change. Our carbon productivity indicator is employed to measure and decompose the carbon productivity changes of 37 major carbon emitting countries and regions over 1995–2009. The main findings include: (i) Endogenous directions identifying the largest improvement potentials are noticeably different from exogenous directions in estimating the inefficiencies of undesirable outputs. (ii) Carbon productivity indicator calculated with the consideration of emission structure provides a more significant estimation on productivity change. (iii) The aggregated carbon productivity and the specific energy driven carbon productivities significantly improve over our study period which are primarily attributed to technical progress. (iv) Empirical results imply that policies focused on researching and developing energy utilization and carbon control technologies might not be enough; it is also essential to encourage technical efficiency catching-up and economic scale management.

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**Key words**: Data envelopment analysis (DEA); Energy driven carbon emissions; Efficiency change; Best practice gap change

## 1 Introduction

Climate change and global warming caused by rising greenhouse gases (GHG) emissions has recurrently aroused public concern (Shao et al., 2011). Environmental problems have become one of the most challenging issues worldwide; especially some developing countries (e.g., China) are concerned with reducing the increasing speeds of energy consumption and GHG (e.g., $CO_2$) emissions while promoting the development of industrialization. The objective of some policies is to keep economic growth under the control of $CO_2$ emissions from the combustion of fossil fuels which is known as the main source of GHG (Liu et al., 2007). Although the community is paying more attention to carbon emissions, most countries will still be dominated by fossil energy consumption in the short term considering their resources endowment and relative low speed of renewable energy research and development (Armaroli and Balzani, 2014; Wang et al., 2013a,b). Therefore, many scholars have stated this dilemma using the evaluation of carbon performance, namely, carbon efficiency and productivity instead of traditional evaluation of energy performance so as to provide deeper insights into the climate policy making and prior actions choosing for energy conservation, emission control and economic growth.

The concept of carbon productivity was proposed by Kaya and Yokobori (1999). They defined it as the amount of GDP generated by per ton of $CO_2$ emissions, denoting the economic benefits of per unit $CO_2$ emissions. The measure of carbon productivity helps to reveal the level of low carbon economy for a country and the corresponding development stage of it. He et al. (2010) pointed that the speed of carbon productivity growth could be used to assess the effort and effectiveness of responding global climate change of a country. This point of view has also been recognized by some other researchers. For instance, Stern and Jotzo (2010) identified the relationship between carbon productivity and economic performance; Bhattacharyya and Matsiimura (2010) decomposed carbon productivity change into a contribution of climate, a residual technology variable, and an input and output mix; Davidsdottir and Fisher (2011) further extended this concept to GDP intensity of GHG emissions. In order to provide a more comprehensive understanding of global carbon productivity changes, the current study provide an estimation of carbon productivity[2] changes for 37 major emitting countries and regions, and the sources for carbon productivity change are additionally identified and discussed.

Previous studies usually use Malmquist–Luenberger productivity index to evaluate carbon productivity change. The Malmquist–Luenberger productivity index, which was proposed and modified by Caves et al. (1982) and Färe et al. (1992), has three disadvantages: (i) productivity index is not circular; (ii) infeasible situation is existing;

[2] In our study, carbon productivity is defined as the total factor carbon emissions productivity which calculates the total factor productivity with the consideration of $CO_2$ emissions as an undesirable output. For expression convenience, we use the shortened form “carbon productivity” in the following text.

and (iii) there are different measures for cross-period observations when computing and decomposing the index (Färe and Grosskopf, 1996). In order to solve these shortages, Berg et al. (1992) proposed an index using a base period technology frontier. It satisfies circularity and has only one measure on cross-period observations, but it still has infeasible situation. Shestalova (2003) introduced a sequential period technology frontier approach. This index produces a single measure of adjacent period data and is immune to infeasibility. But it ignores the technical regress and also fails circularity. Färe et al. (2001) and Zhou et al. (2010) used windows analysis technique to overcome the infeasible situation problem; however this method still pays for the other two shortcomings. Pastor and Lovell (2005) presented a global Malmquist index with all period data. Their index satisfies circularity and generates a single measure for cross-period observations, as well as is immune to infeasible solution. Many studies have been employed global index in empirical analysis. For instance, Oh (2010) utilized global and conventional technology frontier for a comparative analysis of 26 OECD countries. Fan et al. (2015) proposed the global Malmquist–Luenberger index to investigate the performance of $CO_2$ emissions. Zhang and Choi (2013) and Zhang and Wei (2015) evaluated the total factor carbon emissions performance by combining global frontier and meta-frontier so as to take the group heterogeneity into consideration. In our paper, we extend their index to a global Luenberger carbon productivity indicator for measuring carbon productivity change. It has an addictive structure rather than a ratio form to characterize the carbon productivity change.

When measuring the productivity change with the consideration of both intend or desirable outputs (e.g., product or service) and unintended or undesirable outputs (e.g., pollution), the Luenberger productivity indicator is usually calculated by directional distance function (DDF). Shephard (1970) first proposed the distance function, which proportionally expands desirable and undesirable outputs in the feasible region. Then, Chambers et al. (1996) introduced the directional distance function to simultaneously extend desirable outputs and shrink undesirable outputs or some energy inputs. It can be considered that the directional distance function is a generalized form of the distance function. Since the use of fossil energy will inevitably generate unintended outputs (e.g., $CO_2$ emissions), DDF approach is considered a powerful tool in modeling energy and environmental efficiency and productivity (Managi and Jena, 2008; Oggioni et al., 2011; Picazo-Tadeo et al., 2014). Moreover, Zhang and Choi (2014) presented a review regarding the recent applications of DDF in energy and environmental efficiency studies.

In most applications of DDF, the directional vectors typically are predetermined by researchers (i.e., exogenous directions). This is considered a sort of arbitrary and unreasonable for capturing the largest improvement potentials on inputs and outputs. Therefore, some recent studies have focused on inquiring a proper direction to the production frontier. Peyrache and Daraio (2012) proposed an approach to investigate how to obtain the most appropriate directional vector of DDF, whereas Färe et al. (2013) and Hampf and Krüger (2014) present a model based on exogenous normalization constraints. These endogenous directions, which can identify the largest improvement under the existing technology, are more reasonable in a sense and considered to be one of the most promising methods in determining the directions. In this analysis, we introduce the endogenous model by Hampf and Krüger (2014) in to our calculation of global Luenberger carbon productivity indicator.

To the best of our knowledge, previous studies on identifying the sources of carbon productivity change mainly focused on the decomposition of carbon productivity change into, for example, efficiency change and technical change (David and Paul, 1996; Mahlberg and Sahoo, 2011; Chang et al., 2012; Mahlberg and Luptacik, 2014; Woo et al., 2015). In this study, including the investigation of carbon productivity indicator from the traditional decomposition perspective mention above, we further investigate the carbon productivity change from a perspective of additionally identifying the contribution of specific desirable and/or undesirable output factors (e.g., $CO_2$ emissions from the consumption of specific energy). We name this analysis as disaggregation, which is considered a complement of decomposition analysis.

It is important to explore the carbon productivity change from the decomposition perspective, since the carbon productivity change has at least two effects on economic development. First, decomposition could provide some useful information on policy formulation for low carbon economic. Second, it is a guideline for technology improvement. Therefore, in this study, on the one hand, the carbon productivity indicator is decomposed into pure efficiency change (*PEC*), scale efficiency change (*SEC*) and best practice gap change (*BPC*) so as to help identifying the effects of catching-up and technical progress in carbon productivity growth. However, on the other hand, the global Luenberger carbon productivity indicator itself is not capable of reflecting the contribution of individual output sources. Thus, in this study, the outputs are disaggregated in a way that makes us to measure the contribution of individual output sources to productivity change. The output sources include desirable outputs, i.e., gross outputs of industry (GO), and undesirable outputs, i.e., different energy (e.g., coal, oil and natural gas) consumption driven $CO_2$ emissions.

For discussion convenient, in this study, we name the global Luenberger carbon productivity indicator with the consideration of carbon emissions structure (i.e., total $CO_2$ emissions are disaggregated into different energy driven $CO_2$ emissions) as aggregated carbon productivity indicator (*ACPI*), and name the indicator without the consideration of carbon emission structure as integrated carbon productivity indicator (*ICPI*). According to different desirable output factor and fossil fuel driven carbon emissions factors, we further disaggregate *ACPI* into carbon productivity indicator for GO (*GCPI*), coal driven carbon productivity indicator (*CDPI*), oil driven carbon productivity indicator (*ODPI*), and natural gas driven carbon productivity indicator (*NDPI*).

The remainder of this paper is organized as follows. Section 2 presents the endogenous directional distance function model, and describes global Luenberger carbon productivity indicator and its sources. Section 3 introduces the data sources and their calculation methods. Section 4 first shows the comparative results of carbon efficiency measures from endogenous DDF model and two exogenous DDF models; then it provides an empirical analysis based on *ACPI* and its decomposition and disaggregation for 37 major emitting countries and regions. Section 5 provides the conclusions and discussions of this study.

## 2 Methodology

### 2.1 Carbon efficiency evaluation

Assume that we have a set of $j$=1,2,...,$n$ decision making units (DMU$_j$) (i.e. the major emitting countries or regions in this study), which use an input vector $\boldsymbol{x} \in \boldsymbol{R}_+^i$ to produce a desirable output vector $\boldsymbol{y} \in \boldsymbol{R}_+^s$ and a undesirable output vector $\boldsymbol{u} \in \boldsymbol{R}_+^r$. The production possibility set can be expressed as follows:

$$\boldsymbol{T}=\left\{\left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}\right) \in \boldsymbol{R}_+^{i+s+r} : \boldsymbol{x} \text{ can produce } \left(\boldsymbol{y},\boldsymbol{u}\right)\right\} \qquad (1)$$

$\boldsymbol{T}$ is often assumed to satisfy the standard axioms: (i) convexity (Shephard, 1970); (ii) inputs and desirable outputs are strongly disposable (Färe and Primont, 1995); (iii) undesirable outputs are weakly disposable associated with desirable outputs (Färe and Grosskopf, 2004); and (iv) desirable and undesirable outputs are null-joint. The latter three axioms can be expressed as follows:

$$\begin{aligned}
&\textit{If } \left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}\right) \in \boldsymbol{T} \textit{ and } \boldsymbol{x}' \geq \boldsymbol{x}, \textit{then } \left(\boldsymbol{x}',\boldsymbol{y},\boldsymbol{u}\right) \in \boldsymbol{T}; \text{ or } \textit{if } \left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}\right) \in \boldsymbol{T} \textit{ and } \boldsymbol{y}' \leq \boldsymbol{y}, \textit{then } \left(\boldsymbol{x},\boldsymbol{y}',\boldsymbol{u}\right) \in \boldsymbol{T}\\
&\textit{If } \left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}\right) \in \boldsymbol{T} \textit{ and } 0 \leq \theta \leq 1, \textit{then } \left(\boldsymbol{x},\theta\boldsymbol{y},\theta\boldsymbol{u}\right) \in \boldsymbol{T}\\
&\textit{If } \left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}\right) \in \boldsymbol{T} \textit{ and } u = \boldsymbol{0}, \textit{then } \boldsymbol{y} = \boldsymbol{0}
\end{aligned}$$

Axiom (iii) means that any proportional decrease of desirable and undesirable outputs together is feasible; while axiom (iv) indicates that if desirable outputs are produced then some undesirable outputs must be generated.

Färe et al. (1989) introduced the weakly disposable undesirable outputs in evaluating the performance of production process. Then Chambers et al. (1996) and Chung et al. (1997) first proposed to examine environmental efficiency by directional distance function (DDF) which seeks to expand the desirable outputs and contract inputs and/ or undesirable outputs simultaneously. The output-oriented DDF is defined as:

$$\vec{\boldsymbol{D}}\left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u};\vec{g}\right) = max\left\{\beta : \left(\boldsymbol{x},\boldsymbol{y}+\beta\vec{g}_y,\boldsymbol{u}-\beta\vec{g}_u\right) \in \boldsymbol{T}\right\} \qquad (2)$$

where $\beta$ is the inefficiency measure. A DMU is considered inefficient if $\beta > 0$ and as efficient if $\beta = 0$.

The method for estimating directional distance function generally can be divided into two categories: the parametric approach (e.g., stochastic frontier analysis) and the non-parametric approach (e.g., data envelopment analysis). The parametric approach (Kumbhakar and Lovell, 2000), which is usually used for measuring inefficiency and shadow prices of pollutants, requires an assumption on the form of production function. Examples of the applications of this method can be found in Färe et al. (2005), Vardanyan and Noh (2006), Matsushita and Yamane (2012) and Zhang et al. (2014). The data envelopment analysis (DEA) technique has an advantage that it does not need a pre-chosen specific form of production function, and it is based on the construction of all piecewise liner combination of observed inputs and outputs. DEA based approach has been widely utilized to examine the energy and environmental efficiency and productivity (Zhou et al. 2008; Shortall and Barnes, 2013; Wang et al., 2012; Wang et al., 2013c; Wang and Wei, 2014). In this paper, we also use the non-parametric DEA approach for evaluation[3].

## 2.2 Endogenous direction selection

In most applications of directional distance function, the directional vectors $\vec{g}_y$ and $\vec{g}_u$ have be predetermined by the researchers, i.e., they are exogenous directions. Two commonly used directions are (i) observation value direction (*OVD*), i.e., $(\vec{g}_y, \vec{g}_u)$ = ($\boldsymbol{y}$, $\boldsymbol{u}$), and (ii) unit value direction (*UVD*), i.e., $(\vec{g}_y, \vec{g}_u)$ = (**1**, **1**). The associated DEA models based on *OVD* and *UVD* for computing the inefficiency score $\beta$ for each DMU$_j$ are presented as follows:

$$
\begin{aligned}
& \max_{\beta,\lambda} \ \beta \\
\text{s.t.} \quad & \boldsymbol{x}_j \geq \boldsymbol{X}\lambda \\
& \boldsymbol{y}_j + \beta \boldsymbol{y}_j \leq \boldsymbol{Y}\lambda \\
& \boldsymbol{u}_j - \beta \boldsymbol{u}_j = \boldsymbol{U}\lambda \\
& \beta,\ \lambda \geq 0
\end{aligned}
\qquad (3)
$$

$$
\begin{aligned}
& \max_{\beta,\lambda} \ \beta \\
\text{s.t.} \quad & \boldsymbol{x}_j \geq \boldsymbol{X}\lambda \\
& \boldsymbol{y}_j + \beta \leq \boldsymbol{Y}\lambda \\
& \boldsymbol{u}_j - \beta = \boldsymbol{U}\lambda \\
& \beta,\ \lambda \geq 0
\end{aligned}
\qquad (4)
$$

In Models (3) and (4), $\boldsymbol{\lambda}$ is the intensity variable; $\boldsymbol{X}$ denotes the $i \times n$ matrix of inputs; $\boldsymbol{Y}$ denotes the $s \times n$ matrix of desirable outputs; whereas $\boldsymbol{U}$ denotes the $r \times n$ matrix of undesirable outputs. The first and second inequality restrictions represent the strong disposability of inputs and desirable outputs, while the equality restriction indicates weak disposability of undesirable outputs.

The above two predetermined directions expand the intended outputs and contract the unintended outputs with the same rate, i.e., they provide conventional radial efficiency measures. In practice, these two measures are considered somewhat arbitrarily with less economic or policy meaning in efficiency evaluation. Another

[3] One shortcoming of traditional DEA approach is the lack of statistical inference. By using the bootstrapping technique, this problem can be partially overcome (Simar and Wilson, 1999; Zhang et al., 2015). This technique is immune to the uncertainty from the sampling variation of the production frontier. Thanks to the reviewer for pointing out this issue.

weakness is that the radial efficiency measure may underestimate the inefficiency of a DMU when there are non-zero slacks (Fukuyama and Weber, 2009). In addition, the choosing of *OVD* or *UVD* is not capable of identifying the largest efficiency improvement potentials, and the inefficiency scores calculated from *UVD* would further be affected by the units of inputs and outputs, i.e., the inefficiency measure from *UVD* is not unit invariant. Moreover, Picazo-Tadeo and Prior (2009) and Murty et al. (2012) pointed out that the utilization of weak disposability assumption can even lead to a downward-sloping segment on the efficiency frontier, and thus some inefficient observations would be classified as efficient along with the above two exogenous directions. To solve these problems, several studies have extended a new approach which adjust different outputs with different rates, namely, the non-radial DDF (e.g., Färe and Grosskopf, 2010; Zhou et al., 2012; Barros et al., 2012). It disaggregates the inefficiency of DMU for each specific input and output factor. From the perspective of identifying the slacks and being free from the unit scaling problem on efficiency measurement (Färe et al., 2007), the non-radial DDF is considered more favorable than the radial DDF. However, traditional non-radial DDF still cannot deal with the downward-sloping situation of frontier or identify the largest efficiency improvement potentials. Therefore, Färe et al. (2013) developed an endogenous direction based on exogenous normalization constrains, i.e., maximizing the inefficiency measure of DMU under evaluation over the directional vectors. In this study, we name the endogenous direction as *ED*. Furthermore, Hampf and Krüger (2014) explored a more general method to endogenously seek the directions along which each DMU can identify the largest efficiency improvement potentials. Both of the above two measures extend non-radial DDF and make it immune to the shortcomings of the conventional radial efficiency measures. The associated DEA model based on the *ED* for computing the inefficiency score $\beta$ for each DMU$_j$ is presented as follows:

$$\begin{aligned}
&\max_{\beta,\lambda,\alpha,\delta} \quad \beta \\
s.t.\quad & \boldsymbol{x_j} \geq \boldsymbol{X}\lambda \\
& \boldsymbol{y_j} + \beta\alpha \otimes \boldsymbol{y_j} \leq \boldsymbol{Y}\lambda \\
& \boldsymbol{u_j} - \beta\delta \otimes \boldsymbol{u_j} = \boldsymbol{U}\lambda \\
& \boldsymbol{1}^T \alpha + \boldsymbol{1}^T \delta = \boldsymbol{1} \\
& \beta, \lambda, \alpha, \delta \geq 0.
\end{aligned} \qquad (5)$$

In Model (5), " $\otimes$ " is the Hadamard product for two vectors. The vectors $\alpha$ and $\delta$ are the different weights for desirable and undesirable outputs, respectively, and the associated non-negative restrictions on $\alpha$ and $\delta$ imply that only the directions that do not reduce desirable outputs or increase undesirable outputs are chosen. The inefficiency score for specific desirable output $y_h$ ($h$=1,2,...,$s$) is $\beta_{y_h}$, and the inefficiency score for specific undesirable output $u_k$ ($k$=1,2,...,$r$) is $\beta_{u_k}$. They can be set up as:

$$\beta_{y_h} = \beta\alpha_{y_h}, h=1,2,\ldots,s \qquad (6)$$

$$\beta_{u_k} = \beta\delta_{u_k}, k{=}1,2,\ldots,s \qquad (7)$$

where $\alpha_{y_h}$ and $\delta_{u_k}$ represent the weight of desirable output $y_h$ and undesirable output $u_k$.

Thus, we have $\beta = \sum_{h=1}^{s}\beta_{y_h} + \sum_{k=1}^{r}\beta_{u_k} = \sum_{h=1}^{s}\beta\alpha_{y_h} + \sum_{k=1}^{r}\beta\delta_{u_k}$.

To utilize the endogenous directions instead of the predetermined exogenous direction are considered more reasonable in efficiency measure, because the DMU under evaluation along the endogenous directions presented in Model (5) can capture the furthest distance to the efficiency frontier, namely, it can identify the largest efficiency improvement potentials under the current technology.

### 2.3 Global Luenberger productivity indicator calculation

As mentioned above, traditional Luenberger productivity indicator may encounter the problems of failing circularity, spurious technical regress, infeasible situation and different measures for cross-period DDF (Wang and Wei, 2016). To overcome these weaknesses, we introduce the global production technology to the Luenberger productivity indicator for computing carbon productivity change.

Consider a panel data set of $t$=1,2,...,$T$ time period, a global benchmark technology is defined as $\boldsymbol{T}_C^G = \boldsymbol{T}_C^1 \cup \boldsymbol{T}_C^2 \cup \ldots \cup \boldsymbol{T}_C^T$ or $\boldsymbol{T}_V^G = \boldsymbol{T}_V^1 \cup \boldsymbol{T}_V^2 \cup \ldots \cup \boldsymbol{T}_V^T$ (Pastor and Lovell, 2005). The subscribe $C$ or $V$ denotes the technology exhibiting constant returns to scale (CRS) or variable returns to scale (VRS).

The global Luenberger productivity indicator (*GLPI*) defined on is as follows:

$$\begin{aligned} GLPI_C^G\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t;\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right) &= \vec{\boldsymbol{D}}_C^G\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right) - \vec{\boldsymbol{D}}_C^G\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right) \\ &= \beta_C^G\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right) - \beta_C^G\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right) \end{aligned} \qquad (8)$$

where the directional distance function $\vec{\boldsymbol{D}}_C^G\left(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}\right) = max\left\{\beta : \left(\boldsymbol{x},\boldsymbol{y}+\beta\alpha\otimes\boldsymbol{y},\boldsymbol{u}-\beta\delta\otimes\boldsymbol{u}\right)\in\boldsymbol{T}_C^G\right\}$.

In Eq. (8), the positive, zero, or negative values of $GLPI_C^G$ respectively indicates the global Luenberger productivity growths, remains at the same level, or declines. Similar to the decomposition of Malmquist index and Luenberger indicator by Färe et al. (1994) and Chambers et al. (1996), the can be decomposed into efficiency change (*EC*) and best practice gap change (*BPC*) as showed in Eqs. (9) and (10):

$$EC = \beta_C^t\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right) - \beta_C^{t+1}\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right) \qquad (9)$$

$$BPC = \left[\beta_C^G\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right) - \beta_C^t\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right)\right] - \left[\beta_C^G\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right) - \beta_C^{t+1}\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right)\right] \qquad (10)$$

*EC* is technical efficiency change on cross-period observation, capturing the movement away from or toward the technology frontier. *BPC* is technology change, measuring a change in the best practice gap between the global technology frontier and each period technology frontier. The efficiency change can be further decomposed into pure efficiency change (*PEC*) and scale efficiency change (*SEC*). Here, scale efficiency means the deviation from the existing production scale and the optimal scale that produces maximum marginal benefit. *PEC* measures the change of technical efficiency under *VRS* and *SEC* measures the scale efficiency change between two adjacent periods. *PEC* and *SEC* can be computed as follows:

$$PEC=\beta_V^t\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right)-\beta_V^{t+1}\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right) \qquad (11)$$

$$SEC=\left[\beta_C^t\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right)-\beta_V^t\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t\right)\right]-\left[\beta_C^{t+1}\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right)-\beta_V^{t+1}\left(\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right)\right] \qquad (12)$$

Therefore, the sum of the three components (*PEC*, *SEC* and *BPC*) is equal to *GLPL*:

$$GLPI_C^G\left(\boldsymbol{x}^t,\boldsymbol{y}^t,\boldsymbol{u}^t;\boldsymbol{x}^{t+1},\boldsymbol{y}^{t+1},\boldsymbol{u}^{t+1}\right)=PEC+SEC+BPC \qquad (13)$$

At last, we point out that for the individual output carbon productivity indicators (i.e., *GCPI*, *CDPI*, *ODPI* and *NDPI*) and their decomposition, they can be obtained corresponding from Eqs. (8), (10), (11) and (12) with the individual inefficiency scores of desirable output and three specific energy driven carbon emissions outputs. Note that the positive (or negative) values of *PEC*, *SEC* and *BPC* respectively indicate pure efficiency improvement (or deterioration), scale efficiency increase (or decrease), and technical progress (or regress). All zero values on *PEC*, *SEC* and *BPC* indicate no changes.

## 3 Data

Our analysis relies on a panel data of world's 37 major emitting countries and regions over the periods 1995–2009 which are collected from World Input–Output Database (WIOD). WOID has been used to analyze the effects of socio-economic development, environmental pressures and globalization on trade patterns across a wide range of countries. In our sample, each of these 37 major emitting countries and regions has two inputs (i.e., labor and capital), one desirable output (i.e., gross outputs of industries, GO) and three undesirable outputs (i.e., coal driven $CO_2$ emissions, oil driven $CO_2$ emissions, and natural gas driven $CO_2$ emissions). We detail the data sources and calculation methods of each variable as follows.

Labor is computed as total hours worked by persons engaged (millions hours) in the industry sector which was originally collected from employment and labor force statistics for each country and region. Capital is the real fixed capital stock which includes investment and capital stocks at constant prices in 1995. It is then transformed into international currency (millions US$) by exchange rate provided in WIOD database. Gross outputs of industry are also calculated in millions US$ at constant prices in 1995. Meanwhile, the aggregated $CO_2$ emissions as well as its components of coal driven, oil driven, and natural gas driven $CO_2$ emissions with respect to carbon emission structure are measured in thousand tons of $CO_2$. We first obtain the coal driven $CO_2$ emissions for each year from sub-item carbon emissions (i.e., hard coal and derivatives, lignite and derivatives, coke) according to the Air Emission Accounts of WIOD. Then we calculate the part of oil driven $CO_2$ emissions for each year using diesel oil for road transport, motor gasoline, jet fuel (kerosene and gasoline), light fuel oil, heavy fuel oil, naphtha and other petroleum products. Finally, the natural gas driven $CO_2$ emissions and derived gas driven $CO_2$ emissions are accumulated into unified natural gas $CO_2$ emissions.

## 4 Empirical analysis

In this section we first provide a comparative analysis between the evaluation result based on endogenous directions (*ED*) and two exogenous directions (i.e., observation value directions and unit value directions). Second, we analyze the global Luenberger carbon productivity indicator with and without the consideration of carbon emission structure. Then we generally illustrate the aggregated carbon productivity indicator, individual carbon emissions productivity indicators, and the decomposition of these carbon emissions productivity indicators. At last, we present and discuss the empirical results on carbon productivity change for different energy consumption group of countries, and for specific countries.

### 4.1 Comparative analysis between endogenous directions and two exogenous directions

We compute the inefficiency scores of all major emitting countries and regions using Models (3)–(5). The results of inefficiency scores on gross outputs of industry, coal driven $CO_2$ emissions, oil driven $CO_2$ emissions, and natural gas driven $CO_2$ emissions with respect to *ED*, *OVD* and *UVD* are presented in Table 1. The average inefficiency scores are arithmetic means of 37 major emitting countries and regions. For all outputs, it can be seen in Table 1 that the national average inefficiency scores under *ED* are the largest. The countries that display the most similar situations are Australia, Russia, Turkey and USA. Their annual average inefficiency scores based on *ED* are far greater than those based on *OVD* and *UVD*. This result verifies that countries and regions can identify the largest efficiency improvement potentials along the endogenous directions.

**[Insert Table 1 here]**

In order to provide a further insight into the method comparison, we apply the Kruskal-Wallis (KW) test to test the null, which assumes the ranks between two methods are the same. The paired comparison results for endogenous direction, observation direction and unit value direction are listed in Table 2. The first four rows are the results for GO. It can be found that the inefficiency scores under *ED* and *OVD* have the same ranks at the 5% level of significance, while *UVD* is significantly different with the other two methods. As can be seen in coal driven $CO_2$ emissions, we reject the null in *ED* vs.

*UVD* and *ED* vs. *OVD*, indicating that the rank of inefficiency scores in endogenous directions is distinct from the other two methods. The test result of natural gas driven $CO_2$ emissions is similar to that of coal driven $CO_2$ emissions. The test result of oil driven $CO_2$ emissions reveals that these three methods differ significantly. This finding indicates that endogenous direction is significantly different from exogenous directions in calculating the inefficiency scores of undesirable outputs which verifies the necessity of alternatively utilizing the endogenous direction based model.

**[Insert Table 2 here]**

### 4.2 Comparative analysis between *ICPI* and *ACPI*

First, we discuss the relationship of global Luenberger carbon productivity indicator with and without consideration of carbon emission structure (i.e., aggregated carbon productivity indicator and integrated carbon productivity indicator) by Model (5). Figure 1 shows the average annual *ICPI* and *AVPI* of 37 countries and regions from 1995 to 2009. It can be seen that these two indicators experience a similar trend. During 1995–2001, they both indicate negative carbon productivity changes, especially for the case of *ACPI*. Then the two indicators show positive growths during 2001–2008 and rapid declines from 2008 to 2009. This may appear to come from the delayed impact of the global financial crisis, and the energy consumption growth is greater than economic growth during this period.

**[Insert Figure 1 here]**

Meanwhile, Figure 1 also illustrates that the absolute value of carbon productivity indicator is basically greater in *ACPI* than *ICPI*. Namely, *ICPI* is higher than *ACPI* when the indicator $< 0$, and *ACPI* is greater than *ICPI* when the indicator $> 0$. This result indicates that the carbon productivity indicator may be underestimated if we do not take carbon emission structure into consideration. In other words, carbon productivity indicator calculated with the consideration of emission structure provides a more significant estimation on productivity change. Therefore, in the following sections we primarily use the carbon productivity indicator with the consideration of carbon emission structure (i.e., *ACPI*) and individual carbon emissions productivity indicators (i.e., *CDPI*, *ODPI* and *NDPI*) for empirical analysis.

### 4.3 General carbon productivity change analysis

According to the emission structure, we disaggregate the total $CO_2$ emissions into coal driven, oil driven, and natural gas driven $CO_2$ emissions, and correspondingly, *ACPI* can be disaggregated into several output specific carbon productivity indicators, namely, *GCPI*, *CDPI*, *ODPI* and *NDPI*. Here, we primarily focus on discussing the contribution of different specific energy driven carbon emissions in carbon productivity change, i.e., the latter three indicators.

Figure 2(a) illustrates the cumulated *ACPI* of 37 countries and regions from 1995 to 2009. It shows that there is an overall upward trend on the aggregated carbon productivity indicator, but the increase trend is not consistent. More specifically, it declines from 1995 to 2000, increases since 2001, whereas shows a drop during 2008–2009. In addition, the cumulated indicator switches from negative to positive since 2005. According to this trend, our study period is further divided into three stages: 1995–2000, 2000–2005 and 2005–2009 in the following discussions.

**[Insert Figure 2 here]**

Figure 2(b) shows the disaggregated carbon productivity indicators of three specific energy driven $CO_2$ emissions from *ACPI*. It can be seen that during 1995-2000, the carbon productivity decreases of all three specific energy driven $CO_2$ emissions together cause the decline on *ACPI*, and in which, *NDPI* is the primary contributor because of its continuous decrease. However, during 2000-2005 and 2005-2008, these three carbon productivity indicators begin to increase, and they together escalate *ACPI*. It also can be seen that the increase patterns of *CDPI*, *ODPI* and *NDPI* are quite similar since 2001, and in which, *ODPI* shows the highest growth rate, but the increase on *NDPI* is still lower than the other two carbon productivity indicators. This finding indicates that since 2001, the oil driven carbon productivity experiences the most significant increase which primarily promotes the aggregated carbon productivity growth.

In order to identify the driving force of the changes on the above carbon productivity indicators, we further decompose these carbon productivity indicators of individual energy driven $CO_2$ emissions into three components of *BPC*, *PEC* and *SEC*. The results are presented in Table 3 which firstly shows that all the individual energy driven carbon productivities experience significant declines during 1995–2000 and significant increases during 2005–2009. Over the entire study period of 1995–2009, the increase on *BPC* promotes the growth of all three specific energy driven carbon productivity indicators, and *BPC* is the primary driving force for the growth of *CDPI* and *ODPI*. This indicates that the gaps between the global and single period technology frontier with regard to the use of coal, oil and natural gas reduce on average, and technical progress (characterized by the decrease on best practice gaps) on the utilization of coal and oil contributes most for the correspondingly carbon productivity growth. In addition, the improvement on *PEC* also positively contributes to all three specific energy driven carbon productivity indicators, but the contributions are relatively small, which indicates that pure efficiency increase (i.e., catching-up effects) on the utilization of coal, oil and natural gas also plays a positive role on carbon productivity growth. At last, *SEC* of all three specific energy driven carbon productivities significantly decreases, indicating that scale efficiency on energy utilization obviously declines and thus decelerates the growths of all three specific energy driven carbon productivities.

**[Insert Table 3 here]**

### 4.4 Carbon productivity change analysis based on energy consumption group of countries

For providing a comparative analysis of the difference in carbon productivity indicators in different countries characterized by specific energy consumption structure, in this section, we classify the 37 major emitting countries and regions into two groups according to each country's or region's dominated consumption of energy resource. These two groups are coal-based group and oil-and-natural gas-based group. Because the oil consumption dominated countries are also characterized by high rate consumption of natural gas (i.e., 14 in 37 countries or regions), and there are only a few countries are dominated by natural gas consumption in our sample (i.e., 3 in 37 countries or regions). Therefore, we combine oil consumption dominated countries and natural gas consumption dominated countries together in one group.

The box plot of average *ACPI* for the two groups during each study period are illustrated in Figure 3. During the period 1995–2000, the median of carbon productivity indicator of oil/natural gas-based group is higher than that of coal-based group, and the average of indicators of coal-based and oil-and-natural gas-based groups are -0.085 and -0.076, respectively. There are 63% countries in the coal-based group and 62% countries in oil-and-natural gas-based group show decrease on carbon productivity, and the decrease in coal-based group is much more obvious than that in oil-and-natural gas-based group.

But this situation reverses in the following period. During 2000–2005, the coal-based group presents higher median and average on carbon productivity indicators than those of the oil-and-natural gas-based group. However, it can be seen that the carbon productivity change of coal-based group slightly regresses during 2005–2009, which may be caused by more severe impact of international finance crisis that stated in 2007 in those coal consumption dominated countries, while the carbon productivity change of oil-and-natural gas-based group slightly increases during the same period. These findings imply that coal consumption dominated countries may be more sensitive on carbon productivity changes when facing economic fluctuations. This phenomenon may be interpreted as those oil-and-natural gas consumption dominated countries have more advanced mature technology on energy utilization and carbon control in their industry sectors. However, most of the coal consumption dominated countries are economically less developed countries and have immature technology on carbon control. Moreover, economic cycles have a violently impact on the industrial sector, and the gross outputs of industrial sector account for a large proportion of GDP in coal consumption dominated countries. Thus these countries will experience a severer shock in the face of economic fluctuations.

**[Insert Figure 3 here]**

In order to achieve a better understanding of the sources of *ACPI* change for the two groups, the decomposition of average *ACPI* into *BPC*, *PEC* and *SEC* is further reported in Table 4. The last row presents that both two groups show the rise in *ACPI* during the entire study period. It can be seen that for most time in the study period, technical progress and pure efficiency improvement are the primary driving forces for the growth of *ACPI*, while scale efficiency changes always provide negative contributions on the growth of *ACPI* both in the coal consumption dominated countries and the oil/natural gas consumption dominated countries. This finding implies that the major emitting countries and regions in this study have failed on average in moving to more optimal scales of producing industry products and emitting carbon emissions, and this regression is more obvious in coal consumption dominated countries. The possible reason is that there are 50% of coal consumption dominated countries are developing countries in our sample which are still in the development stage of industrialization and urbanization. Their economic growth and carbon productivity improvement are mostly driven by investment rather than consumption. Therefore, for these countries, it is necessary to restructure their economic growth mode, accelerate the transformation of industry sectors, improve energy efficiency and optimize the energy consumption structure with a view to efficiently mitigating carbon emissions. Accordingly, policies focused on researching and developing advanced energy utilization and carbon control technologies might not be enough, more efforts are required from policymakers to encourage economic scale management and technical efficiency catching-up among group members.

**[Insert Table 4 here]**

### 4.5 Carbon productivity change analysis for specific countries and regions

In this section, we additionally compare the carbon productivity indicators, including *ACPI* and its three specific energy driven carbon productivity indicators, among the 37 major emitting countries and regions. Figure 4 illustrates the average *ACPI* and its disaggregation indicators (*CDPI*, *ODPI* and *NDPI*) and decomposition indicators (*BPC*, *PEC* and *SEC*) over the entire study period. According to *ACPI*, it can be seen from Figure 4(a) that more than 70% countries and regions whose *ACPI* range from 0.6% to 18% experience carbon productivity growths. Among these countries and regions, China shows the highest average growth rate (17.7%), followed by Luxembourg (14.6%), Austria (10.0%) and Belgium (7.6%). Their carbon productivity growths are all driven by the reduction on best practice gaps, i.e., technical progress. In Figure 4(a), all western European countries show carbon productivity increase, indicating that western European countries still play a significant role in leading carbon productivity growth in the world. Moreover, since China is the largest country of energy consumption and $CO_2$ emissions, the highest growth of carbon productivity implying that it will play an increasing role in the effort of energy conservation and carbon emissions reduction. On the contrary, there are 11 countries and regions show carbon productivity decrease (range from -0.7% to -21.0%) and in which, 5 countries show the most significant productivity declines: Greece, Portugal, Bulgaria, Brazil and Romania. Except for Brazil, the other four countries are all southern and eastern European countries. Their production structure is oriented to industrial activities which produce serious pollutions. Moreover, environmental awareness of citizens and environmental regulations are relatively weak in these countries. *BPC* decrease and *PEC* decrease are the primary driving forces for carbon productivity decline in Greece, Portugal and Romania, while *SEC* decrease primarily causes carbon productivity decline in Bulgaria and Brazil.

**[Insert Figure 4 here]**

Figure 4(b)–(d) further show the decomposition of coal, oil and natural gas driven carbon productivity indicators. Firstly, concerning *CDPI* shown in Figure 4(b), China, Austria, Luxembourg, Lithuania and Latvia show the most obvious coal driven carbon productivity increase, in which, technical progress on energy utilization and carbon control is the primary driving force for the former three countries and scale efficiency increase in the primary driving force for the latter two countries. Technical progress also plays the primary role in coal driven carbon productivity growth in Belgium, Spain, Sweden and France. In addition, the catching-up effect (i.e., pure technical efficiency increase) primarily leads coal driven carbon productivity growth in Russia, Turkey and Canada. Greece and Portugal show the most obvious decline on coal driven carbon productivity, followed by Mexico, Slovenia and Bulgaria.

Secondly, regarding *ODPI* shown in Figure 4(c), most obvious oil driven carbon productivity increases happen in China, Luxembourg and Belgium which are all driven by the promotion on *BPG*, while the most obvious oil driven carbon productivity decreases come from Greece, Bulgaria and Portugal. Technical progress is the largest driving force for 16 countries and regions shown oil driven carbon productivity growth, while pure technical efficiency decrease and scale efficiency decrease are the largest driving force for 6 and 5 countries shown oil driven carbon productivity decline, respectively.

Thirdly, according to *NDPI* shown in Figure 4(d), few countries show natural gas driven carbon productivity growth: Luxembourg, China, Austria, Japan and Belgium, whose productivity growths are all come from technical progress. On the contrary, 12 countries and regions, e.g., Portugal, Greece, Taiwan, Estonia, Brazil, Spain, Bulgaria, Sweden, Korea, Turkey, India and Mexico show natural gas driven carbon productivity decline, and technical regress and scale efficiency decline are the primary driving forces lead this decline. The natural gas driven carbon productivity rarely changes in the remaining 20 countries.

Finally, the above findings indicate that the decrease on best practice gaps, i.e., the progress on technology of energy utilization and related carbon emissions control is the most important driving force for the growths on all three energy specific carbon productivity indicators (*CDPI, ODPI* and *NDPI*), which account for 58%, 68% and 56% of their growths, respectively. In other words, to promote technical progress on energy utilization and carbon control should be assigned priority in policy making and considered the prior action for further promoting carbon productivity. Meanwhile, it is also essential to encourage technical efficiency catching-up and economic scale management. Regarding to specific measures of environmental policy, promoting research and development on energy conservation and carbon emissions reduction technologies would be highly recommended. These measures include transferring low-carbon technologies such as carbon capture, usage and storage (CCUS) technology from developed countries to developing countries, or encouraging the installation and employment of pollutant emission scrubber. Likewise, enhancing management in energy efficiency promotion, such as exploring low-carbon community operation mode, implementing stricter air pollution reduction and carbon emissions control regulations in high-pollution projects, should be considered in the policy making of economic development. Lastly, constructing market based energy conservation and emission control mechanism (e.g., the introduction of carbon emissions trading system as well as resources tax and carbon tax) would also be a reasonable means of improving carbon efficiency and productivity.

## 5 Conclusions

The evaluation of carbon productivity helps to formulate energy and environmental policies and prioritize actions for economic growth, resources saving, and emission reduction, which consequently makes the effort on climate change mitigation and sustainable development accountable. In this study we propose a carbon productivity indicator based on an endogenous directional distance function (DDF) selecting approach and a global Luenberger productivity indicator for computing the carbon productivity changes of 37 major emitting countries and regions worldwide. We additionally investigate the sources of the carbon productivity change from the traditional decomposition perspective of identifying the best practice gap change (i.e., technical progress or regress), pure efficiency change, and scale efficiency change, and from a new disaggregation perspective of additionally identifying the contribution of specific desirable output factor (e.g., gross outputs of industry) and undesirable output factors (e.g., coal driven, oil driven and natural gas driven $CO_2$ emissions) to carbon productivity change.

The global Luenberger carbon productivity indicator is applied to evaluate the carbon productivity change in different energy driven $CO_2$ emissions of 37 major emitting countries and regions over 1995–2009 in this study. The main findings are summarized as follows. (i) The approach of endogenous direction that identifies the largest improvement potentials is significantly different from the approach of exogenous directions in calculating the inefficiency scores of undesirable outputs, and this finding verifies the necessity of alternatively utilizing the endogenous DDF for evaluating carbon efficiency and productivity. (ii) The comparative analysis reveals that the carbon productivity indicator calculated with the consideration of carbon emission structure (i.e., carbon emissions from different energy sources) provides a more significant estimation on carbon productivity change. (iii) On the average of all 37 major emitting countries and regions, the carbon productivity significantly increases over the study period, and the primary driving forces for this increase can be attributed to the decrease of best practice gaps (i.e., technical progress) and pure efficiency improvement (i.e., catching-up effect). However, scale efficiency decrease drags the carbon productivity growth. (iv) Coal consumption dominated countries may be more sensitive on carbon productivity changes than oil and natural gas consumption dominated countries when facing economic fluctuations. (v) Policies focused on promoting advanced energy utilization and carbon control technologies should be assigned priority; while technical efficiency catching-up and economic scale management should also be encouraged for further improving carbon productivity.

**Acknowledgment**

The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China (grant nos. 71471018, 71101011 and 71521002). We also gratefully thank for the reviewers' valuable comments and suggestions.

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## Tables & Figures

**Table 1 Output factor specific inefficiency scores (averages of period 1995-2009)**

| Countries/ regions | Gross outputs of industry | | | Coal driven $CO_2$ emissions | | | Oil driven $CO_2$ emissions | | | Natural gas driven $CO_2$ emissions | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *ED* | *OVD* | *UVD* | *ED* | *OVD* | *UVD* | *ED* | *OVD* | *UVD* | *ED* | *OVD* | *UVD* |
| Australia | 0.511 | 0.124 | 0.005 | 0.948 | 0.124 | 0.026 | 0.306 | 0.124 | 0.042 | 0.886 | 0.124 | 0.101 |
| Austria | 0.247 | 0.187 | 0.015 | 0.578 | 0.187 | 0.520 | 0.085 | 0.187 | 0.189 | 0.770 | 0.187 | 0.324 |
| Belgium | 0.073 | 0.147 | 0.019 | 0.640 | 0.147 | 0.582 | 0.389 | 0.147 | 0.148 | 0.826 | 0.147 | 0.331 |
| Bulgaria | 3.204 | 0.963 | 0.185 | 0.833 | 0.963 | 0.050 | 0.897 | 0.963 | 0.099 | 0.958 | 0.963 | 0.158 |
| Brazil | 0.655 | 0.487 | 0.005 | 0.490 | 0.487 | 0.182 | 0.713 | 0.487 | 0.015 | 0.803 | 0.487 | 0.085 |
| Canada | 0.383 | 0.366 | 0.056 | 0.841 | 0.366 | 0.869 | 0.540 | 0.366 | 0.329 | 0.951 | 0.366 | 0.501 |
| China(mainland) | 0.000 | 0.048 | 0.001 | 0.601 | 0.048 | 0.001 | 0.493 | 0.048 | 0.006 | 0.414 | 0.048 | 0.049 |
| Czech Republic | 0.395 | 0.187 | 0.024 | 0.976 | 0.187 | 0.054 | 0.370 | 0.187 | 0.176 | 0.950 | 0.187 | 0.196 |
| Germany | 0.350 | 0.202 | 0.027 | 0.829 | 0.202 | 0.301 | 0.189 | 0.202 | 0.270 | 0.821 | 0.202 | 0.590 |
| Denmark | 0.368 | 0.307 | 0.020 | 0.794 | 0.307 | 0.305 | 0.477 | 0.307 | 0.125 | 0.790 | 0.307 | 0.504 |
| Spain | 0.554 | 0.420 | 0.028 | 0.769 | 0.420 | 0.548 | 0.353 | 0.420 | 0.208 | 0.813 | 0.420 | 0.805 |
| Estonia | 1.175 | 0.672 | 0.048 | 0.856 | 0.672 | 0.055 | 0.571 | 0.672 | 0.155 | 0.779 | 0.672 | 0.355 |
| Finland | 0.279 | 0.225 | 0.018 | 0.885 | 0.225 | 0.226 | 0.366 | 0.225 | 0.153 | 0.839 | 0.225 | 0.527 |
| France | 0.177 | 0.227 | 0.010 | 0.477 | 0.227 | 0.565 | 0.261 | 0.227 | 0.108 | 0.790 | 0.227 | 0.340 |
| United Kingdom | 0.047 | 0.052 | 0.015 | 0.851 | 0.052 | 0.251 | 0.269 | 0.052 | 0.166 | 0.942 | 0.052 | 0.202 |
| Greece | 0.400 | 0.452 | 0.004 | 0.810 | 0.452 | 0.026 | 0.605 | 0.452 | 0.016 | 0.572 | 0.452 | 0.213 |
| Hungary | 0.868 | 0.495 | 0.104 | 0.929 | 0.495 | 0.491 | 0.567 | 0.495 | 0.399 | 0.977 | 0.495 | 0.310 |
| India | 0.001 | 0.535 | 0.017 | 0.986 | 0.535 | 0.022 | 0.839 | 0.535 | 0.054 | 0.911 | 0.535 | 0.298 |
| Ireland | 0.036 | 0.174 | 0.027 | 0.724 | 0.174 | 0.572 | 0.490 | 0.174 | 0.223 | 0.853 | 0.174 | 0.753 |
| Italy | 0.310 | 0.209 | 0.010 | 0.493 | 0.209 | 0.527 | 0.343 | 0.209 | 0.084 | 0.914 | 0.209 | 0.164 |
| Japan | 0.076 | 0.143 | 0.013 | 0.803 | 0.143 | 0.324 | 0.170 | 0.143 | 0.174 | 0.781 | 0.143 | 0.599 |
| Korea | 0.200 | 0.426 | 0.043 | 0.938 | 0.426 | 0.312 | 0.652 | 0.426 | 0.238 | 0.896 | 0.426 | 0.933 |
| Lithuania | 0.785 | 0.586 | 0.009 | 0.665 | 0.586 | 0.342 | 0.697 | 0.586 | 0.034 | 0.913 | 0.586 | 0.069 |
| Luxembourg | 0.000 | 0.133 | 0.002 | 0.289 | 0.133 | 0.110 | 0.477 | 0.133 | 0.011 | 0.596 | 0.133 | 0.045 |
| Latvia | 0.395 | 0.276 | 0.022 | 0.705 | 0.276 | 0.334 | 0.772 | 0.276 | 0.043 | 0.965 | 0.276 | 0.093 |
| Mexico | 0.459 | 0.412 | 0.012 | 0.762 | 0.412 | 0.242 | 0.849 | 0.412 | 0.022 | 0.959 | 0.412 | 0.081 |
| Netherlands | 0.326 | 0.149 | 0.005 | 0.723 | 0.149 | 0.151 | 0.472 | 0.149 | 0.037 | 0.950 | 0.149 | 0.051 |
| Poland | 0.262 | 0.386 | 0.029 | 0.989 | 0.386 | 0.039 | 0.671 | 0.386 | 0.142 | 0.945 | 0.386 | 0.331 |
| Portugal | 0.274 | 0.298 | 0.018 | 0.679 | 0.298 | 0.357 | 0.468 | 0.298 | 0.111 | 0.643 | 0.298 | 0.581 |
| Romania | 2.084 | 0.874 | 1.045 | 0.525 | 0.874 | 0.420 | 0.875 | 0.874 | 0.425 | 0.975 | 0.874 | 0.393 |
| Russia | 1.099 | 0.198 | 0.073 | 0.618 | 0.198 | 0.043 | 0.868 | 0.198 | 0.050 | 0.986 | 0.198 | 0.022 |
| Slovak Republic | 0.238 | 0.149 | 0.035 | 0.957 | 0.149 | 0.159 | 0.507 | 0.149 | 0.226 | 0.978 | 0.149 | 0.142 |
| Slovenia | 0.059 | 0.403 | 0.043 | 0.920 | 0.403 | 0.248 | 0.726 | 0.403 | 0.195 | 0.896 | 0.403 | 0.866 |
| Sweden | 0.000 | 0.011 | 0.000 | 0.243 | 0.011 | 0.022 | 0.320 | 0.011 | 0.003 | 0.199 | 0.011 | 0.042 |
| Turkey | 0.799 | 0.274 | 0.026 | 0.727 | 0.274 | 0.028 | 0.911 | 0.274 | 0.019 | 0.951 | 0.274 | 0.091 |
| Taiwan | 0.000 | 0.131 | 0.005 | 0.518 | 0.131 | 0.028 | 0.515 | 0.131 | 0.027 | 0.393 | 0.131 | 0.175 |
| USA | 0.221 | 0.115 | 0.056 | 0.924 | 0.115 | 0.500 | 0.476 | 0.115 | 0.444 | 0.927 | 0.115 | 0.873 |
| **Average** | 0.468 | 0.309 | 0.056 | 0.738 | 0.309 | 0.266 | 0.528 | 0.309 | 0.140 | 0.825 | 0.309 | 0.330 |

**Table 2 KW test for inefficiency scores ($H_0$: two methods have the same ranks)**

| Gross outputs of industry | *OVD* | *ED* |
|---|---|---|
| *UVD* | 43.689(0.000) | 41.892(0.000) |
| *OVD* | | -1.797(0.810) |
| Coal driven $CO_2$ emissions | *OVD* | *ED* |
| *UVD* | 4.649(0.534) | 49.230(0.000) |
| *OVD* | | 44.581(0.000) |
| Oil driven $CO_2$ emissions | *OVD* | *ED* |
| *UVD* | 25.622(0.001) | 52.581(0.000) |
| *OVD* | | 26.959(0.000) |
| Natural gas driven $CO_2$ emissions | *OVD* | *ED* |
| *UVD* | 0.311(0.967) | 47.568(0.000) |
| *OVD* | | 47.257(0.000) |

*Note*: Significant level at 5%; numbers without parentheses are test statistics; numbers in parentheses are *P*-value.

**Table 3 Decomposition of specific energy driven carbon productivity indicator**

| Indicators | 1995-2000 | 2000-2005 | 2005-2009 | 1995-2009 |
|---|---|---|---|---|
| *CDPI* | -0.005 | 0.002 | 0.026 | 0.007 |
| *BPC*_coal | 0.007 | 0.007 | 0.018 | 0.010 |
| *PEC*_coal | 0.002 | 0.008 | 0.016 | 0.008 |
| *SEC*_coal | -0.014 | -0.013 | -0.008 | -0.012 |
| *ODPI* | -0.015 | 0.012 | 0.031 | 0.008 |
| *BPC*_oil | -0.006 | 0.021 | 0.027 | 0.013 |
| *PEC*_oil | -0.006 | 0.004 | 0.014 | 0.003 |
| *SEC*_oil | -0.003 | -0.013 | -0.009 | -0.008 |
| *NDPI* | -0.016 | 0.000 | 0.015 | -0.002 |
| *BPC*_natural gas | -0.005 | 0.012 | 0.000 | 0.003 |
| *PEC*_natural gas | 0.005 | 0.008 | 0.013 | 0.008 |
| *SEC*_natural gas | -0.016 | -0.020 | 0.002 | -0.012 |

**Table 4 Average *ACPI* and its decomposition for different energy consumption group**

| | Coal-based group | | | | Oil-and-natural gas-based group | | | |
|---|---|---|---|---|---|---|---|---|
| | *ACPI* | *BPC* | *PEC* | *SEC* | *ACPI* | *BPC* | *PEC* | *SEC* |
| 1995-2000 | -0.086 | -0.093 | 0.117 | -0.109 | -0.076 | -0.022 | -0.032 | -0.022 |
| 2000-2005 | 0.081 | 0.185 | 0.001 | -0.104 | 0.044 | 0.059 | 0.023 | -0.038 |
| 2005-2009 | 0.037 | 0.068 | 0.002 | -0.034 | 0.058 | 0.040 | 0.046 | -0.028 |
| 1995-2009 | 0.011 | 0.053 | 0.040 | -0.082 | 0.009 | 0.026 | 0.012 | -0.029 |

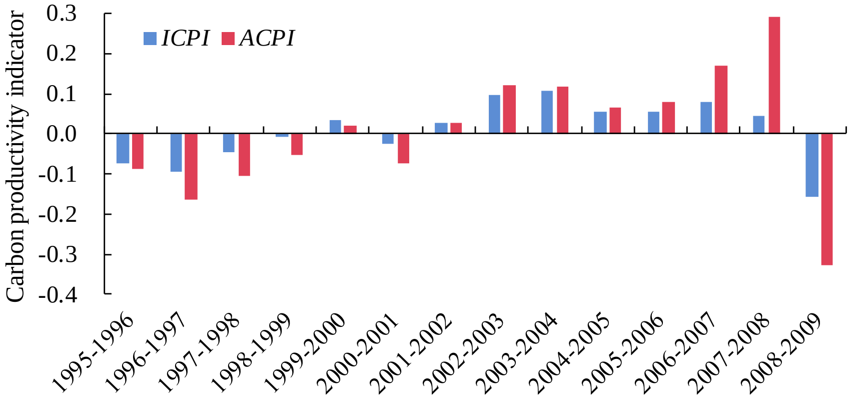



**Figure1 Average annual *ICPI* and *ACPI***

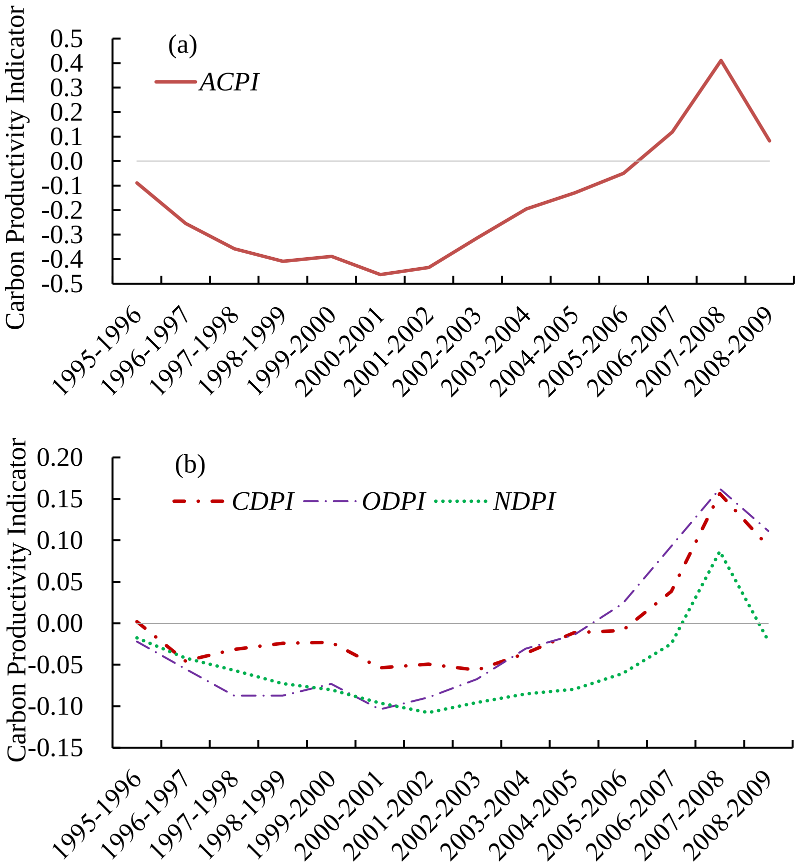



**Figure 2 Cumulated *ACPI* and individual carbon productivity indicators of three energy driven $CO_2$ emissions**

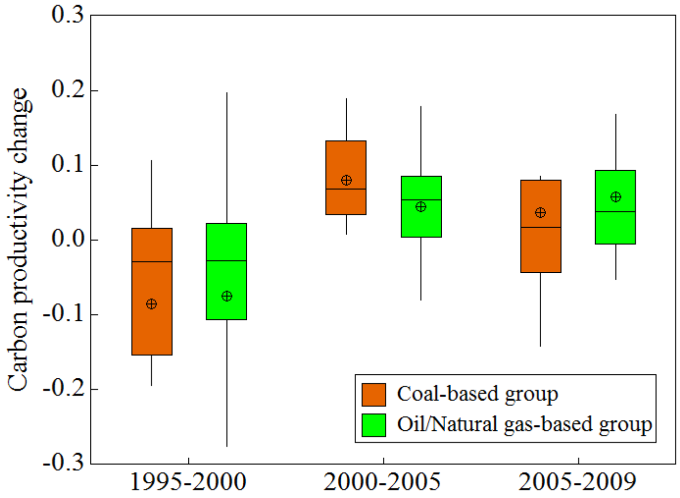
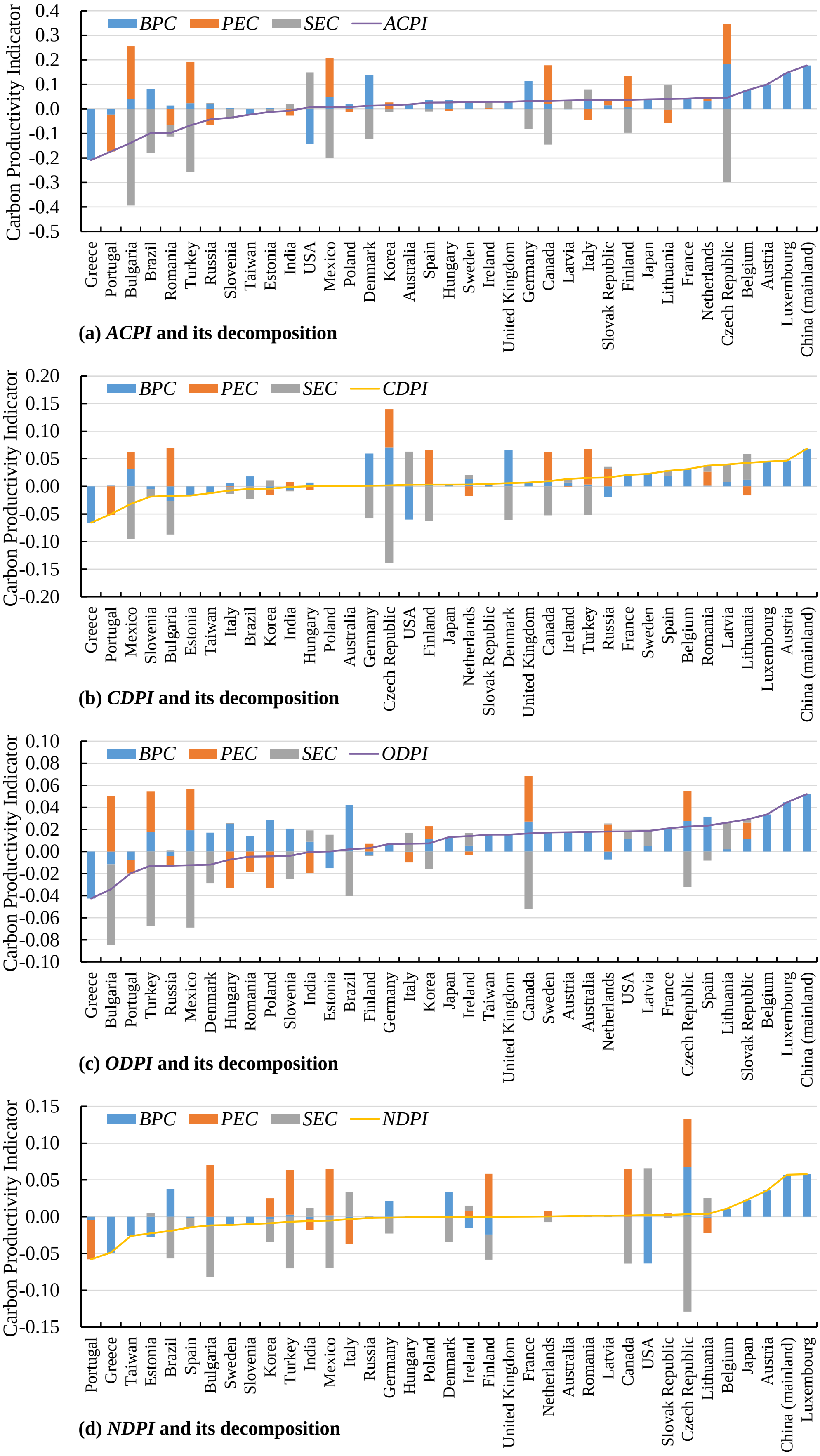



**Figure 3 Box plot of average *ACPI* for different energy consumption groups**




(a) ***ACPI* and its decomposition**

(b) ***CDPI* and its decomposition**

(c) ***ODPI* and its decomposition**

(d) ***NDPI* and its decomposition**

**Figure 4 Carbon productivity indicators for specific countries and regions**